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# Predicting Systems Performance through Requirements Quality Attributes Model

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**Abstract**

Poor requirements definition can adversely impact system cost and performance for government acquisition programs. This can be mitigated by ensuring requirements statements are written in a clear and unambiguous manner that reflects high linguistic quality. This paper introduces a statistical model that uses requirements quality factors to predict system operational performance. This model is created using empirical data from current major acquisition programs within the federal government. Operational Requirements Documents and Operational Test Reports are the data sources, respectively, for the system requirements statements and the accompanying operational test results used for model development. A commercial-off-the-shelf requirements quality analysis tool is used to determine the linguistic quality metrics for the requirements statements. Following model construction, cross validation of the data is employed to confirm the predictive value of the model. In all, the results establish that requirements quality is indeed a predictive factor for end system operational performance; and the resulting statistical model can inform requirements decisions based on likelihood of successful operational performance.


Selection and peer-review under responsibility of the University of Southern California.

*Keywords:* Requirements Engineering; Requirements Quality Attributes; Natural Language Requirements; Systems Engineering

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## 1. Introduction

### *1.1 Problem Statement*

Requirements definition and quality have historically been problematic areas within the systems engineering process; and there is ample research indicating that errors, gaps, and ambiguities in requirements contribute to system deficiencies, incomplete system test plans, and unsatisfactory system performance. Recent technical journal literature[1,2,3] is replete with discussion describing the need for better natural language requirements quality attributes. In addition, a litany of Government Accountability Office (GAO) reports have been written highlighting the preponderance of poor requirements development and management in government acquisition programs; and, moreover, this has been such a significant issue that the 2009 Weapon Systems Acquisition Reform Act explicitly requires the Department of Defense (DoD) to address and improve its performance requirements. Despite the widespread acknowledgement that poor requirements quality leads to “downstream” issues with defects and performance, the problem remains.

This problem, however, could be better managed if there were a means to predict the probability of successful end-system operational performance following requirements development. This would enable quick identification of deficient requirements needing remedy based on their adverse impact on performance. As such, the focus of this research is to address the hypothesis that end-system operational performance can be determined through use of predictive modeling based on requirements quality factors. While the contemporary literature presents head-to-head comparisons of competing tools or processing techniques for improved requirements analysis[4,5], and qualitatively discusses requirements quality impact on defects and the efficacy of various defect prediction methods[6,7,8], there is limited discussion on the impact of requirements quality on operational performance. The research presented in this paper is intended to bridge the gap in the prevailing body of knowledge by providing empirical evidence of the predictive relationship between requirements quality and end-system operational performance.

### *1.2 Approach*

The approach presented in this paper describes on-going doctoral research for developing a statistical model of the relationship between requirements quality factors and system operational test results; hence, analysis and results are in progress. The research methodology involves gathering empirical data from current major acquisition programs within two United States government agencies, DoD and Department of Homeland Security (DHS), to support model development and validation. Operational Requirements Document (ORD) Key Performance Parameters (KPPs) and Operational Test Reports from DoD and DHS serve as the data sources, respectively, for the system requirements statements and the accompanying operational test results. A commercial-off-the-shelf requirements quality analysis tool is used to determine the linguistic quality metrics for the requirements statements. The quality metrics for the requirements statements and the associated operational test results are then used to construct the model. Following model construction, sensitivity analysis is performed, and cross validation of the data is employed to confirm the predictive value of the model. In all, the results are expected to establish that requirements quality is indeed a predictive factor for end system operational performance.

### *1.3 Contributions Summary*

This research on the predictive relationship between requirements quality and system performance provides the following major contributions:

- Predictive Modeling Development Methodology – Section 2
- Statistical Significance of Requirements Quality Relationship to System Performance – Section 3
- Additional Areas of Research for Predictive Modeling – Section 4

## 2. Methodology

Statistical modeling based on empirical performance data is the approach used to address the research hypothesis presented in this paper. The model development and validation methodology involve the following sequential steps as illustrated in Figure 1.

- Obtain ORD KPPs and Operational Test Report results from DoD and DHS acquisition databases
- Analyze KPPs for linguistic quality
- Perform logistic regression on linguistic quality metrics and operational test results
- Develop predictive model based on logistic regression results
- Validate model for predictive performance

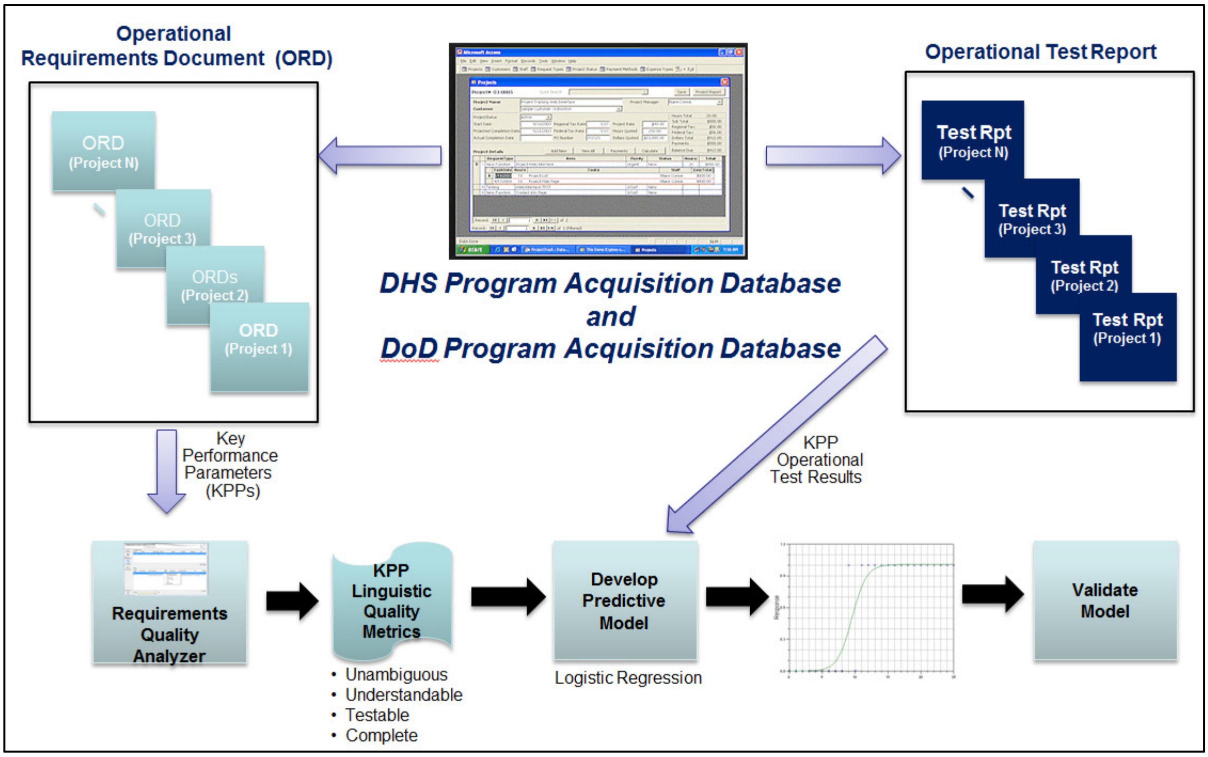


Fig. 1. Methodology Overview

Further discussion on this methodology as well as the analysis tools used for linguistic quality analysis and model construction are described in Section 2.1 and Section 2.2, respectively.

### *2.1 Model Construction and Validation*

Development of a predictive model is required to demonstrate that end-system operational performance can be projected based on the requirements linguistic quality factors as defined below:

- Unambiguous – requirement statement has no more than one interpretation
- Understandable – requirement statement is readily comprehended by the end-user
- Testable – requirement statement has a process to verify requirement has been satisfied
- Complete – requirement statement fully captures requirement parameters

The linguistic quality factors listed above, while not exhaustive, have been selected for use in this research since they are generally accepted as characteristics of good requirements[9].

Several modeling options such as Bayes classifier, logistic regression, and support vector machine may be considered for development of the predictive model in this investigation[10,11]. Given 1) the requirements linguistic quality factor data listed above are categorical and serve as independent or explanatory variables for the model, and 2) the dependent response variable, "operational performance met", is binary, binary logistic regression is the preferred modeling approach[12,13].

Use of empirical data is critical for development of the predictive model. As such, the DHS and DoD program acquisition databases are accessed to provide the ORD KPPs and the KPP operational test results that serve as the data sources for this research. Over 200 key performance parameter requirements statements and the associated operational test results are used for model creation. These requirements statements are imported into an automated requirements analysis tool to calculate the linguistic quality metrics for each statement. In addition, the operational test reports associated with each ORD are reviewed to determine if performance was met for each of the key performance parameters used in the model. These data are then used in a binary logistic regression analysis to determine the linear predictor, or model, for predicting system performance.

Next, a sensitivity analysis is conducted on each of the independent input variables, or linguistic quality factors, used for model construction. The objective of this analysis is to assess the uncertainty in each input parameter. This allows determination of the amount of change in model behavior given a change in the input variable as well as which input variables have the most substantive impact on model performance. The results of the analysis are used to adjust or calibrate the model as necessary.

Lastly, K-fold cross-validation[14,15], a common technique for confirming predictive model performance, is used to assess how the model will generalize to an independent data set. This method involves dividing the data into K subsets, and executing the cross validation over K iterations. One of the K subsets will be used as the test set and the other K-1 subsets will form the training set for each iteration. The advantage of this approach is that it does not depend heavily on which data points are in the training set and which ones are in the test set.

*2.2 Analysis Tools*

Requirements analysis can be accomplished through expert judgment, techniques such as Case-Based Reasoning[16], or use of automated analysis tools[17,18]. According to a recent empirical study completed by Lami[19], automated requirements analysis tools can be more effective than human reviews for finding defective requirements. As such, the research presented in this paper utilizes an automated tool to determine linguistic quality metrics. Although there are numerous commercially available requirements analysis tools such as the Quality Analyzer for Requirement Specifications, Requirements Quality Analyzer, and TigerPro, the CassBeth Specification Analysis Tool was selected for use in this research given its simple user interface, minimal computer resource requirements, and adjustable analysis parameters. CassBeth provides an automated method to review requirements specifications and identify faults in the requirements statements. These defects include poorly worded statements that are ambiguous, vague, untestable, and incomplete. The tool runs on the personal computer and accepts Microsoft Word or text file inputs for the requirements statements. In addition, the tool contains a complete service library with the following options:

- Requirements Text Analysis
- Key Requirements Analysis
- Duplicate Objects Analysis
- Domain Capabilities Analysis
- Generic Capabilities Analysis

The research discussed in this paper uses the CassBeth tool's Requirement Text Analysis service to assess linguistic quality of the key performance parameter statements found in the DHS and DoD ORDs. This service utilizes a default rule set to analyze word and phrase patterns that typically result in less than optimal requirements. However, the default rule set can be tuned if necessary to encompass user-specified instructions. Following import of the key performance parameter statements, the tool generates a report that identifies the linguistic quality defects, if any, in each key performance parameter statement. These results are binary; each quality metric (ambiguous, vague, untestable, and incomplete) is either defective or non-defective. In turn, these binary results serve as the independent variables for the logistic regression model. A screen shot of the CassBeth tool is provided in Figure 2 below.

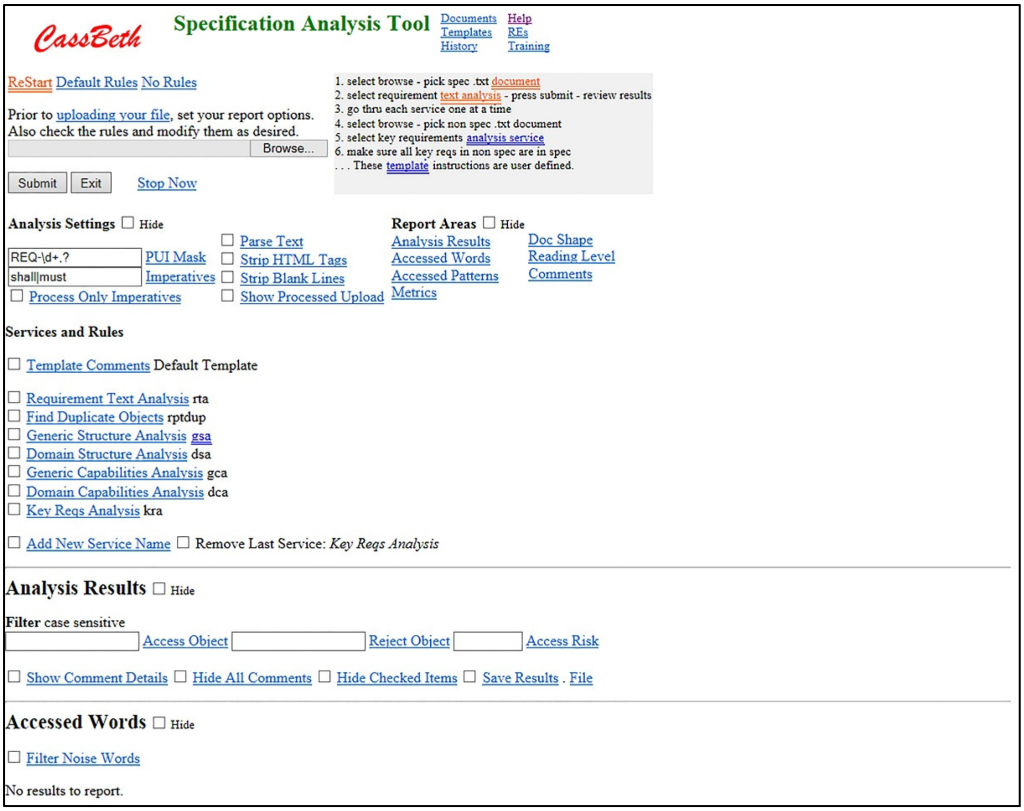


Fig. 2. Specification Analysis Tool

The data analysis for this research is facilitated through use of the Minitab statistical software tool and the MATLAB high-level language and interactive environment. Requirements linguistic quality metrics determined by the CassBeth Specification Analysis Tool are input into Minitab for statistical analysis. Specifically, Minitab performs the binary logistic regression on the metrics data to determine the linear predictor model, statistical significance, and the odds ratio. Minitab also generates the graphs and tables resulting from the logistic regression analysis. Lastly, MATLAB is used to perform the K-fold cross validation.

## 3. Preliminary Observations and Expected Conclusions

This paper conveys the hypothesis and methodology for on-going doctoral research regarding predictive systems performance modeling; hence, analysis and results are in progress. However, the preliminary observations and expected conclusions from this research are presented in the following paragraphs.

### *3.1 Preliminary Observations*

Subsets of ORD and Operational Test Report data obtained from the DHS and DoD acquisition databases combined with fictitious linguistic quality metrics were input in the Minitab statistical analysis tool to perform a trial binary logistic regression analysis. The analysis resulted in a toy model used to gain insights on data requirements and the research hypothesis. Initial observations revealed that multicolinearity of two of the linguistic quality input variables impacted solution convergence within Minitab. This was resolved by removing one of the co-linear input variables from the model. Based on results from the development and exercise of the toy model, no additional data or hypothesis revisions are required at this stage of the research.

### *3.2 Expected Conclusions*

In all, the research is expected to show a statistically significant relationship between requirements quality and system performance and demonstrate that binary logistic regression analysis can be appropriately applied in this area for predictive modeling. The intended value of this research is to offer empirical evidence of the need and benefit of providing increased emphasis and detail for developing high-quality requirements statements. However, additional research and practical use is required to verify that this model can be used as a front-end risk tool to inform requirements decisions based on insight gained on likelihood of successful operational performance.

## 4. Future Research

There are several areas of prospective research to further the investigation described in this paper. These areas include model enhancement, alternative modeling approaches, and piloting. Table 1 below further describes these research areas.

Table 1. Future Research Summary

| Research Area | Methodology |
|---|---|
| **Model Enhancement** | • Enhance the binary logistic model developed in this research with additional data points<br>• Consider using data from other government agencies such as NASA and the FAA |
| **Alternative Modeling Approaches** | • Use alternate prediction models<br>• Consider Support Vector Machine, Bayes Classifier, or K-Nearest Neighbor |
| **Piloting** | • Pilot use of the model in a new systems engineering project<br>• Utilize model as front-end risk management tool and assess how its use impacts changes/improvements in requirements statements |

Conduct of the future research described in this section will enhance model validity and provide additional verification that insight on probability of successful operational performance based on predictive modeling can influence requirements decisions on the front end of the systems engineering process.

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